IMPROVING QUALITY

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USE OF NEURAL NET MODELS FOR STATISTICAL ANALYSIS AND REGULATION OF GLASS RIBBON FORMATION ON TIN MELT

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A method for constructing and applying neural-net models for analyzing and regulating the conditions for glass ribbon formation on tin melt is examined. In this method models are constructed on the basis of neural nets describing the dependence of the indicators of glass properties on the regime and controllable variable input parameters. An algorithm for adjusting the regime variables as a function of the thickness of the glass ribbon produced is developed taking account of changes occurring in the effects which are under observation.

Market competition is forcing glass works makers devote a great deal of attention to the problem of quality. Quality improvements increase production efficiency, lowering costs and increasing market share. The present article examines a method for constructing and using neural-net models for analyzing and regulating the conditions for the formation of glass ribbon on tin melt.

The work is envisaged:

construction of models, based on neural nets, describing the dependence of glass property indicators on regime and controllable variable input parameters;

development of an algorithm for adjusting the regime variables as a function of the thickness of the glass ribbon produced, taking account of changes in the effects being monitored.

The operation of the float-tank in a 630 metric tons/day process line was analyzed. Statistical information about the operation of the process line over one year was used for the analysis.

The quality of glass ribbon formation was evaluated on the basis of both the magnitude of the optical distortions visible in reflected light (grating) and transmitted light (“zebra”) as well as the thickness variations. These characteristics were measure by the procedure described in GOST 111–2001.

The “zebra” measurements of optical distortion were performed at three points along the width of a glass ribbon. Since the measurements were found to be strongly correlated with one another, this made it possible to evaluate the optical distortions according to measurements performed at a single point — the right-hand edge of the glass ribbon.

The distortions seen in reflected light were measured at four points along the width of the glass ribbon. As a result of the strong correlations between the measurements, a decision was made to confine attention to a selection of informative grating indicators on two sections from the right-hand edge of the ribbon along the course of the production line.

The thickness variation of the glass ribbon was measured at five points (small sections) along the width of the ribbon. The strong correlation between the measurements made it possible to evaluate this indicator at three points along the width of the glass ribbon from the right-hand edge along the course of the production line.

To decrease the dimension of the problem, investigations were performed to determine the stochastic correlations between the velocities of the edging machines and the temperatures of tin in the float-tank aisles. After the analysis representative pulses for the velocities of the first and third edging machines and the tin temperatures in the 1st, 12th, and 20th aisles, the oxygen content in the gas atmosphere of the float tank, the temperature of the glass ribbon at the exit from the float tank, and the thickness of the glass ribbon produced were selected.

Previous investigations have shown that neural nets such as a multilayer perceptron can be used to describe glass ribbon formation [1]. A three-layer of variant of a net with backward error feed according to the Levenberg – Marquardt method was used [2]. The number of neurons in the first layer corresponds to the number of input variables, and there

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is one neuron in the last layer (number of output variable). A computational experiment was performed to choose the number of neurons in the hidden layer and the length of the training and testing samples. The number of neurons in the hidden layer was taken to be 20, 35, and 45. The length of the training sample was varied from 15 to 90 days. The ratio of the training to test sample lengths was 0.5, 1.0, and 1.5.

The accuracy of the model was determined by comparing the output data from the neural net with the real data, i.e., according to the variance of the error. Limits determined by the accuracy of the measurements of the property indicators of the glass were added to the variance of the error (Table 1).

The experiment was performed on a sample consisting of 365 averaged daily-average indicators of the glass ribbon formation process. First the neural net was trained on a sample of fixed length n_o, and then it was tested on a subsequent sample of length n_t (Fig. 1). The variance of the experimental error was calculated, after which the weights of all neural nets were set to zero. The average variance of the error of the model for the structure being studied was calculated from the results of four experiments.

A computer experiment showed that increasing the number of neurons in the hidden layer to more than 35 does not make the model more accurate while decreasing it affects the increase of the error variance. Likewise, increasing the length of the training sample to more than 30 days does not decrease the estimated value.

A neural net with the following parameters was chosen to unify the models describing the quality indicators for glass:

number of neurons in the intermediate layer 35;
length of training sample 30 days;
length of test sample no more than 30 days.

To develop neural-net models the variables previously used in regression models were chosen as the influential factors [3]. Neural-net models describing the following dependences were synthesized:

optical distortions visible in transmitted light (“zebra”):

$$Z(t) = Z(\Theta_1(t), \Theta_{12}(t), v_{\mathrm{EFM}}(t), \mathrm{C}_{\mathrm{O}_2}(t), \delta(t));$$

optical distortions visible in reflected light (grating):

$$D_i(t) = D_i(\Theta_{12}(t), \Theta_{20}(t), \Theta_{\mathrm{out}}(t), \delta(t));$$

thickness variation of the glass ribbon:

$$Th_j(t) = Th_j(\Theta_1(t), \Theta_{12}(t), v_{\mathrm{EFM}}(t), \delta(t));$$

TABLE 1.

Glass property indicators	Absolute measurement error	Variance of measurement error
Grating, mm	1	0.25
Thickness variation, mm	0.01	0.000025
“Zebra”, ...°	5	6.25

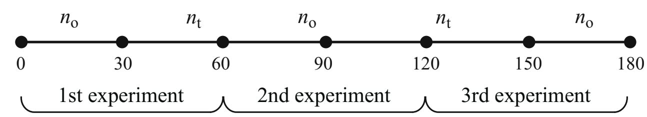

Fig. 1. Example of an experiment with 30-day training and testing samples.

re-heating power:

$$P_{\mathrm{rh}}(t) = P_{\mathrm{rh}}(\Theta_1(t), \Theta_{12}(t), \Theta_{20}(t), \Theta_{\mathrm{out}}(t)),$$

where Θ_1, Θ_{12}, and Θ_{20} are the tin temperatures in the 1st, 12th, and 20th aisles; v_{EFM} is the velocity of the first edge-forming machine; $\mathrm{C}_{\mathrm{O}_2}$ is the oxygen content in the protective atmosphere of the float-tank; Θ_{out} is the temperature of the glass ribbon at the exit from the float-tank; δ is the thickness of the glass ribbon; t is the time, in days; D_i are the values of the grating indicators at two points along the width of the glass ribbon from the right-hand edge along the product; Th_j are the values of the thickness variation at three points along the width of the glass ribbon from the right-hand edge along with the product.

The regulation of the glass ribbon formation process can be viewed as a problem of increasing the quality of the glass by adjusting the parameters of the formation regime with minimum expenditures on electricity for repeated heating. In addition, limitations determined by the GOST 111–2001 requirements are imposed on the magnitude of the optical distortions and thickness variation.

The control actions are the tin temperature in the aisles and the glass ribbon temperature at the exit from the float-tank. The temperature regime for glass ribbon formation was determined by simulation — planning of a computational experiment with neural-net models using the simplex method of optimization. The following problem was solved — the cost must be minimized at each control step:

$$\mathrm{C} = \min P_{\mathrm{rh}}(\Theta_1, \Theta_{12}, \Theta_{20}, \Theta_{\mathrm{in}}, \Theta_{\mathrm{out}}, \delta),$$

where C is the cost of re-heating the glass ribbon and Θ_{in} is the temperature of the glass ribbon at the entrance into the float-tank.

TABLE 2.

Indicator	Value		Variation step	
	minimum	maximum	average	maximum
Tin aisle (right-hand side) temperature, °C				
1st	970	1050	3.7	63.5
12th	760	830	9.6	59.8
20th	580	650	2.3	14.0
Glass ribbon temperature at the float-tank exit, °C	570	640	2.2	29.0

TABLE 3.

Indicator	Manual regulation		Automatic regulation algorithm	
	average value	standard deviation	average value	standard
Optical distortions (“zebra”), ...°	63.5	5.2	67.2	3.0
Optical distortions (grating), mm	6.7	3.4	4.1	1.3
Ribbon thickness variation, mm:				
first part	0.05	0.05	0.02	0.02
second part	0.03	0.02	0.02	0.02
Tin aisle temperature, °C:				
1st	1005.5	6.3	1002.0	3.1
12th	796.0	13.5	790.4	1.1
20th	616.1	5.2	605.5	0
Re-heating power, kW	66.3	94.0	64.4	86.6

The limits on the glass quality indicators were as follows:

$$Z(\Theta_1(t), \Theta_{12}(t), v_{\mathrm{EFM}}(t), \mathrm{C}_{\mathrm{O}_2}(t), \delta(t)) \geq 50°;$$

$$D_i(\Theta_{12}(t), \Theta_{20}(t), \Theta_{\mathrm{out}}(t), \delta(t)) \leq 4 \text{ mm}, i = 1.2;$$

$$Th_j(\Theta_1(t), \Theta_{12}(t), v_{\mathrm{EFM}}(t), \delta(t)) \leq 0.1 \text{ mm}, j = 1, 2, 3;$$

The search for the temperature regime was conducted within the ranges shown in Table 2.

The efficiency of the algorithm for automatic control of the glass ribbon formation process was evaluated by simulating the operation of the system with real data collected from the process line over a period of one year. The comparative results of a simulation with manual regulation of the glass ribbon formation process are presented in Table 3.

The proposed regulation algorithm is distinguished by high tin temperature stability in the float-tank aisles. This algorithm makes it possible to increase the quality of the glass produced by decreasing the standard deviation of the optical distortions seen in transmitted and reflected light as well as the standard deviation of the thickness variations. At the same time the average grating size, thickness variation of the glass ribbon, decreases and the average “zebra” size increases. The reheating power decreases by 2.9%.

The present investigations have shown that the glass quality can be further increased and the process costs can be decreased by using neural nets for statistical analysis and regulation of the glass ribbon formation regime on tin melt.

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